Exploiting Structure in Parsing to 1-Endpoint-Crossing Graphs

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Abstract

Deep dependency parsing can be cast as the search for maximum acyclic subgraphs in weighted digraphs. Because this search problem is intractable in the general case, we consider its restriction to the class of 1endpoint-crossing (1ec) graphs, which has high coverage on standard data sets. Our main contribution is a characterization of lec graphs as a subclass of the graphs with pagenumber at most 3. Building on this we show how to extend an existing parsing algorithm for 1-endpoint-crossing trees to the full class. While the runtime complexity of the extended algorithm is polynomial in the length of the input sentence, it features a large constant, which poses a challenge for practical implementations.

1 Introduction

Motivated by applications in natural language understanding, recent work in dependency parsing has targeted 'deep' graphs, a term used to refer to representations that are not necessarily tree-shaped. Such graphs support intuitive analyses of argument sharing in control constructions, quantification, and semantic modification, among others. Data sets of deep dependency graphs are often derived from the derivations of expressive grammar formalisms; for an overview, see Kuhlmann and Oepen (2016).

Deep dependency parsing has been formalized as the search for maximum acyclic subgraphs in weighted digraphs (Schluter, 2014; Kuhlmann and Jonsson, 2015). Because this problem is known to be intractable in the general case (Guruswami et al., 2011), it is interesting to identify structural restrictions on the target graphs that can yield polynomial-time parsing algorithms without sacrificing too much of the empirical coverage. Schluter (2015) and Kuhlmann and Jonsson (2015) propose to address deep dependency parsing under the restriction that the target structures should be *noncrossing*, a constraint related to projectivity as known from syntactic parsing. When the search space is restricted to the class of noncrossing graphs, maximum subgraph parsing is possible in time $O(n^3)$, where n is the length of the input sentence. Unfortunately, the restriction to noncrossing graphs excludes a large proportion of the linguistic data. It seems clear that deep dependency parsing, much more than syntactic parsing, needs algorithms that can handle graphs with crossing arcs.

An interesting weaker restriction than the noncrossing condition is the restriction to graphs which are 1-endpoint-crossing (Pitler et al., 2013), a constraint originally formulated for tree-shaped graphs. The maximum 1-endpoint-crossing subtree of a weighted digraph can be found in time $O(n^4)$. In this paper we show how to generalize this result to non-trees. This is not straightforward, as the obvious modification of existing algorithm for trees turns out to be incomplete for general graphs. The key to a complete algorithm, and our main technical contribution, is a characterization of 1-endpointcrossing graphs as a certain subset of the class of graphs with pagenumber at most 3 (Section 3). The exact characterization refers to the restricted patterns in which arcs can cross each other. From this characterization we obtain an $O(n^5)$ algorithm for general graphs (Section 4). When a certain, rare type of crossing configurations is ruled out, the runtime complexity of the algorithm reduces to $O(n^4)$, the same as for trees.

While the runtime of both new algorithms is polynomial in the length of the input sentence, both feature large constants, which leads us to discuss challenges in extending our algorithm into a practical parser for deep dependency parsing (Section 5).



Figure 1: A sample dependency graph (Flickinger et al., 2016, CCD #20604004), drawn as an arc diagram. Note that each word is meant to represent one endpoint. (We leave some space between different arcs that share a common endpoint.) To save some space we draw arcs as semi-ellipses rather than semi-circles. The graph has pagenumber 3 and is 1ec.

2 Background

We start by giving some background on the classes of graphs that we study in this paper.

2.1 Graph Classes

A *dependency graph* for a natural language sentence x is an acyclic digraph whose vertices are in one-to-one correspondence with the words in x.¹ A sample dependency graph is shown in Figure 1. To draw a dependency graph, we place its vertices on an invisible line in the plane according to their left-to-right order, and draw each arc as a semi-circle in the half-plane bounded by that line. We refer to this type of drawing as an *arc diagram*. Given an arc diagram of a dependency graph, two arcs of the graph are said to *cross* if their corresponding semi-circles intersect in points other than a common endpoint.

A dependency graph is called *noncrossing* if its arc diagram does not feature crossing arcs. Noncrossing graphs have also been called 'planar' (Titov et al., 2009). We can generalize the noncrossing condition by allowing arcs to be drawn not only in the half-plane above the vertex line but also in that below it, or in any of some fixed number k of half-planes bounded by the vertex line. This type of graph drawing is known as a *book* embedding (Bernhart and Kainen, 1979). (We may picture the half-planes as the pages of a book, and the vertex line as the book spine.) The pagenumber of a graph is the smallest number k for which the graph has a crossing-free book embedding with k half-planes (pages). The graph in Figure 1 has pagenumber 3. Graphs whose pagenumber is at most k have also been called 'k-planar' (Gómez-Rodríguez and Nivre, 2010).

Our main interest in this paper is in the class of 1-endpoint-crossing graphs. A dependency graph is called *1-endpoint-crossing (1ec)* if for each of its arcs a, all arcs that cross a share a common endpoint (Pitler et al., 2013). The graph in Figure 1 is 1ec. The 1ec property was originally formulated for dependency trees, but the definition carries over to more general graphs without modifications.

2.2 Empirical Coverage

We assess the emprical coverage of 1ec graphs on a standard data set, the data used for the 2015 Sem-Eval Task on Broad-Coverage Dependency Parsing (Flickinger et al., 2016). This data consists of token-aligned dependency graphs from four distinct linguistic traditions, dubbed DM, PAS, PSD, and CCD. For details about these target representations we refer to Oepen et al. (2016).

Table 1 gives the percentages of complete graphs (G) and individual arcs (A) that can be covered under the restriction to noncrossing graphs, graphs with bounded pagenumber (≤ 2), and 1ec graphs.² We see that the coverage of 1ec graphs clearly surpasses that of noncrossing graphs on all four representation types. Noncrossing graphs in fact seem to be a rather poor match for the data, especially on CCD, where it rules out more than half of the target graphs. With respect to pagenumber, even the low bound at ≤ 2 achieves very highest coverage, the highest among the three classes considered. The class 1ec is on average 2.11 percentage points behind in terms of coverage on complete graphs and 0.14 points on individual arcs.

¹We restrict our attention to unlabelled dependency graphs.

²Arc coverage was calculated using a brute-force algorithm that removes the minimal number of arcs needed to make the remaining graph satisfy the relevant property.

class		DM	PAS	PSD	CCD
nc	G	69.29	59.85	65.04	49.53
	А	97.63	97.24	96.01	95.83
$pn \le 2$	G	99.46	99.48	97.64	98.33
	А	99.97	99.97	99.76	99.89
1ec	G	97.30	97.18	95.85	96.16
	А	99.83	99.85	99.60	99.75

Table 1: Coverage in terms of complete graphs (G) and individual arcs (A) for noncrossing graphs, graphs with pagenumber at most 2, and 1ec graphs.

2.3 Parsing Complexity

While high coverage is desirable, it often goes hand in hand with high parsing complexity. As already mentioned in the introduction, the maximum noncrossing subgraph can be found in time $O(n^3)$, where n is the length of the input sentence. The corresponding problem for the class of graphs with pagenumber at most 2 is NP-hard (Kuhlmann and Jonsson, 2015), which means that the high coverage of this class incurs a considerable price to pay. The relatively high coverage of 1ec graphs observed in Table 1 suggests that this class of graphs might strike a good balance between coverage and complexity.

3 The Structure of 1ec Graphs

In this section we derive the structural characterization of 1ec graphs that we will exploit in our parsing algorithm. Our point of departure is the result of Pitler et al. (2013, Theorem 1) that 1ec trees have pagenumber at most 2. This result does not carry over to general graphs; in fact we have already seen an empirical example of a 1ec graph with pagenumber 3 in Figure 1.

Lemma 1 *There are lec graphs with pagenumber 3.*

Our first goal is to prove that pagenumber 3 is also the *maximal* pagenumber of 1ec graphs. To show this we will characterize 1ec graphs in terms of their *crossing graphs*.

3.1 Pagenumber of 1ec Graphs

The *crossing graph* of a dependency graph has a vertex corresponding to each arc, and an edge between two vertices if and only if the corresponding arcs cross. The crossing graphs of noncrossing dependency graphs consist of isolated vertices. Crossing graphs are interesting because the pagenumber of a dependency graph equals the *chromatic number* of its crossing graph, the smallest number of colours needed to colour the vertices of the crossing graph in such a way that no two neighbouring vertices share the same colour. From a *k*-colouring of its crossing graph we obtain a crossing-free *k*-book embedding of the dependency graph by placing two arcs on the same page if and only if their corresponding vertices are coloured with the same colour. This correspondence has previously been studied by Gómez-Rodríguez and Nivre (2010) and Kuhlmann and Jonsson (2015), among others. The following lemma is due to Pitler et al. (2013, Lemma 2).

Lemma 2 *The crossing graphs of lec graphs do not contain triangles (cycles of length 3).*

PROOF Suppose for the sake of contradiction that there exists a cycle *abca*. The arcs *a* and *c* must share an endpoint, as they both cross *b*. Because of this, they cannot cross, and therefore cannot be adjacent in the cycle.

We use this lemma in the proof of the following:

Lemma 3 The pagenumber of lec graphs is at most 3.

PROOF We show that the crossing graph of a 1ec graph is 3-colourable. To colour the crossing graph, we separately colour each of its components (also crossing graphs). We distinguish two cases:

- The component does not contain a cycle, or contains cycles of length at most 4. By Lemma 2, the component does not contain a triangle, and therefore no odd cycle at all. We can therefore 2-colour the component by traversing the component using depth-first search and assigning to each vertex the opposite colour of its parent in the search tree.
- 2. The length of the shortest cycle in the component is at least 5. In the graph theory literature, our crossing graphs are better known as *circle graphs*, and the length of the shortest cycle in a graph is known as its *girth*. It has been shown that every circle graph with girth at least 5 is 3-colourable (Ageev, 1999).

Thus in each case, 3 colours suffice to colour the component, and hence the complete graph.



Figure 2: Counter-clockwise from top: dependency graph, chord diagram, crossing graph.

3.2 Isolation Property for Cog Belts

lec graphs with pagenumber 3 (or subgraphs thereof) have a characteristic structure reminiscent of the teeth of a cogwheel; a minimal example is shown at the top of Figure 2. The proof of Lemma 3 also reveals that these graphs correspond to cycles of length 5 or more in the crossing graph. Because of this we will refer to these graphs as *cog belts*. Our aim for the remainder of this section is to show (in Lemma 6) that these structures are 'isolated', in the sense that no arcs other than the arcs in the cog belt can cross the cog belt. This property will be the key to the parsing algorithm in Section 4. To show it we study the relation between crossing graphs and *chord diagrams*.

The *chord diagram* of a dependency graph is obtained by placing the vertices of the graph on the boundary of a circle such that their clockwise order extends the left-to-right order in the original graph, and drawing each arc of the graph as a chord of the circle. An example is given in Figure 2. Note that the chord diagram representation does not contain information about the direction of the arcs of the dependency graph, and cannot be used to recover the exact linear positions of the vertices. Importantly though, we can still read off the crossing graph of a dependency graph from its chord diagram.

To prove the maximality property, we will reason about the chord diagram corresponding to a crossing graph. In general, this diagram is not uniquely determined. However, when we restrict ourselves to 'strict' chord diagrams in which there are exactly twice as many endpoints as there are chords, then there are certain crossing graphs that have a *unique* such chord diagram (up to symmetry).³ In particular, this holds for cycles of length at least 5. We start by proving a lemma about another type of graphs with unique strict chord diagrams. A *domino* is a graph of the form $\Box \Box$.

Lemma 4 *The crossing graphs of lec graphs do not contain dominoes.*

PROOF For the sake of contradiction, suppose that the crossing graph of a lec graph G contains a domino. The arcs that correspond to the vertices on this domino induce a subgraph of G. We reason about how the chord diagrams for this induced subgraph could look like. A domino has a unique 'strict' chord diagram (Gabor et al., 1989); this diagram looks as shown in the left half of Figure 3. However, this chord diagram cannot be the actual chord diagram of a lec dependency graph. For example, the chord b is crossed by chords a and d, but these chords do not share a common endpoint. We can try to 'repair' the chord diagram (without changing the underlying crossing graph) by merging some of the endpoints; in particular, we can merge the two endpoints a_2 and d_1 into one endpoint that we may refer to as ad, which removes one violation of the 1ec property at chord b. Eliminating as many violations as possible, we obtain the modified chord diagram in the right half of Figure 3. However, even in this diagram there are still some violations left: Apart from a and d, the chord b is also crossed by e, and this chord cannot be made to share an endpoint with a and d. We therefore conclude that the crossing graph of Gdoes not contain a domino.

For our next lemma we need some terminology from geometry. A *polygram* is a non-convex regular polygon, drawn by connecting a given number of points placed at equal distance on the boundary of a circle. Polygrams can be denoted by its *Schläfli symbol* $\{p/q\}$, where p gives the number of corners, and q states that each corner should be connected to its neighbours q steps away. For example, $\{5/2\}$ denotes the pentagram in Figure 2.



Figure 3: Proof of Lemma 4

³These are exactly the graphs that are *prime* with respect to split decompositions; see Gabor et al. (1989).



Figure 4: Proof of Lemma 6, illustrated using a cycle of length m = 9. The additional chord (red-dashed) violates the 1ec property: In the graph on the *left*, it creates additional endpoints for the chords 13, 29, 35, and 46; in the graph in the *middle*, it creates additional endpoints for the chords 46 and 57; in the graph on the *right*, the new chord is crossed by 13 and 46, which do not share an endpoint.

Lemma 5 The chord diagram of the subgraph induced by a cycle of length $m \ge 5$ in a crossing graph of a lec graph is unique (up to symmetry) and forms a polygram $\{m/2\}$.

PROOF Similar to the proof of Lemma 4, we reason about how the chord diagrams for the subgraph induced by a cycle of length $m \ge 5$ in a crossing graph of a 1ec graph could look like. We illustrate our argument using concrete cycles, *abcdea* (m = 5) and *abcdefa* (m = 6). The strict chord diagrams for these examples look as follows.



Again, these diagrams cannot be chord diagrams of 1ec dependency graphs; for example, the chord b is crossed by chord a and c, which do not have a common endpoint. The only way to repair the chord diagrams without changing the underlying crossing graph is to merge the two endpoints a_1 and c_1 into a common endpoint which we shall refer to as ac, and likewise for all the other chords. This yields the following (non-strict) chord diagrams:



The left diagram is the pentagram $\{5/2\}$, the right diagram is the hexagram $\{6/2\}$ (6 corners, each of which is connected to the neighbour 2 steps away).

From these examples it is not hard to generalize to arbitrary values of m: If m is odd, then the chord diagram for the cycle forms a regular star polygon. If m is even, then the chord diagram forms a regular polygon compound consisting of two copies of a regular, convex (m/2)-gon.

Pitler et al. (2013, Lemma 3) show that any odd cycle of length $m \ge 5$ in a crossing graph of a 1ec graph uses at most m vertices in the original graph. From Lemma 5 we get the stronger result that *any* cycle of length $m \ge 5$ uses *exactly* m vertices.

We are now ready to prove the isolation property:

Lemma 6 Any cycle of length $m \ge 5$ in a crossing graph of a lec graph forms a connected component of that graph.

PROOF (SKETCH) The proof is by induction on m. We start by using the construction in the proof of Lemma 5 to obtain the polygram chord diagram for the cycle. We then suppose, for the sake of contradiction, that one of the vertices on the cycle has an incident edge that does not itself belong to the cycle, and reason about how to update the chord diagram. The new edge could either go to another on the cycle or to a new vertex. The second alternative would require us to add a new chord to the diagram. However, we can convince ourselves that any new chord will necessarily violate the 1ec property (see Figure 4). For the first alternative, we distinguish three cases: If m = 5, then adding a 'shortcut' edge to another vertex on the cycle will create a triangle, which is ruled out by Lemma 2. If m = 6, then adding a shortcut will create either a triangle or a domino, which is ruled out by Lemma 4. Finally, if $m \ge 7$, then adding a shortcut will create either a triangle, a domino, or a cycle of length $m \ge 5$, of which we may assume that it forms a connected component.

4 Parsing Algorithm

In the previous section we have characterized lec graphs in terms of their crossing graphs. In this section we will exploit this characterization to show how to obtain a parsing algorithm for lec graphs. We follow Kuhlmann and Jonsson (2015) in casting dependency parsing as a maximum subgraph problem: Given an arc-weighted digraph G, our aim is to find a subset of arcs with maximum total weight such that the induced subgraph is lec. The weights of G should be learned from data.

4.1 Relaxed Deduction System for 1ec Trees

To obtain a parsing algorithm for 1ec graphs, an obvious idea is to take the corresponding algorithm for trees (Pitler et al., 2013) and 'relax' it by deleting all book-keeping that is used to enforce the tree constraint. We present the resulting algorithm as a *weighted deduction system* (Shieber et al., 1995; Nederhof, 2003). Such a system uses *inference rules* to derive information about sets of graphs; this information is represented by weighted formulas called *items*. Parsing amounts to finding the derivation of a *goal item* with maximum weight, starting from a set of *initial items*.

We assume that we are given an arc-weighted digraph G = (V, A) with vertices $V = \{1, \ldots, n\}$. Items represent subgraphs of G corresponding to either *isolated intervals* [i, j], where there are no arcs between vertices in the open interval (i, j) and vertices outside of [i, j], or isolated crossing regions $[i, j] \cup \{x\}$, where there are i) no arcs between vertices in (i, j) and vertices outside of $[i, j] \cup \{x\}$, and ii) no arcs between the external vertex x and vertices in (i, j) that are crossed by arcs with both endpoints in (i, j). Isolated intervals are represented by items of the form Int[i, j], and isolated crossing regions are represented by four different types of items that put a constraint on whether arcs from xinto (i, j) may be crossed by arcs inside of [i, j]with endpoints at the left border (L[i, j, x]), the right border (R[i, j, x]), both borders (LR[i, j, x]), or none of the two borders (N[i, j, x]). The initial items of the system correspond to one-vertex subgraphs and take the form Int[i, i]. The goal item is Int[1, n], representing the complete graph that spans all vertices. Finally, the inference rules are shown in Figure 6. The weight of the item on the left-hand side of each rule is computed as the sum of weights of the items on the right-hand side and, if specified, the weight of a new arc.



Figure 5: Non-completeness for general 1ec graphs. Splitting the item LR[1, 5, 6] at k = 3 using rule (11) makes it impossible to retain the arc $2 \leftarrow 4$.

4.2 Non-Completeness for General Graphs

A deduction system is *correct* with respect to a class of graphs \mathcal{G} if each of its derivations denotes (under an intended interpretation) a graph from \mathcal{G} (*soundness*), and every graph from \mathcal{G} has some derivation (*completeness*). While the algorithm of Pitler et al. (2013) is correct for the class of lec trees, it turns out that its relaxed version is *not* correct for the full class of lec graphs. More specifically, there are some lec graphs that do not have derivations in the relaxed system.

To illustrate the problem, we consider the cog belt in Figure 5 and reason backwards, reading inference rules as rules for *decomposing* a subgraph into smaller ones. The only way to decompose the example graph from an *Int* item is to instantiate rule (6) with k = 5. This removes the dashed arc $5 \rightarrow 1$, leaving the rest of the graph inside an *LR* item. Now to decompose the *LR* item we need to find a 'split vertex' $k \in (1,5)$ for rule (11), creating items L[1, k, 6] and R[k, 5, 6]. However, splitting the graph in this way makes it impossible to retain arcs that cover k – and inside the interval (1, 5)*every* vertex is covered by some arc. This property prevents the decomposition of not only the graph in Figure 5, but more generally every cog belt.

4.3 Correctness for Graphs without Cog Belts

While the relaxed deduction system is not correct for general 1ec graphs, we can prove that it is correct for the class of all 1ec graphs that do not contain cog belts. The proof is straightforward but tedious, so here we content ourselves with sketching the structure and giving the most central intuitions.

Soundness To show that every derivation denotes a lec graph without cog belts, we use induction over the length of the derivation. The property obviously holds for the initial items. For the inductive case we need to check that the structural property is preserved by each rule. This is not hard to see with respect to the lec constraint, which is

Figure 6: The rules of the 'relaxed' deduction system, following the basic rules of Pitler (2013). The scores for arcs s[i, j] do not specify the arc's direction (we simply choose the arc with the higher weight). The indices may not overlap, giving rise to rule (6), the special case of rule (5) for l = j.

inherited from the tree-based system. Showing that the rule applications cannot result in cog belts is slightly more complicated. However, we can convince ourselves that the constraints implied by the item types and the constraints on the accessibility of vertices implied in the rules are sufficient to exclude the forbidden structures. In particular, a derivation cannot 'remember' the vertex that would be needed to close off a cog belt (see Figure 7).

Completeness To show that every 1ec graph without cog belts can be derived by the system, we use induction on the size of the graph, where size is measured as the total number of vertices

and arcs. Graphs with size 1 (one vertex) are represented by the initial items. For the inductive case we need to check that every graph which satisfies the structural property is decomposable by some rule. We can use the same strategy as Pitler (2013), who classifies graphs into a number of templates and for each of those templates shows which rule can be applied to it. In particular we need to show that the subgraphs gained in each decomposition adhere to the intended interpretations, and that all arcs can be added. The important observation is that, if the graph does not contain a cog belt, then the information represented in each item is sufficient to build all arcs (see Figure 8).





Figure 7: When attempting to derive this cog belt right-to-left we could instantiate rule (8) as $Int[1, 6] \leftarrow s[1, 3] + R[1, 2, 3] + Int[2, 3] + L[3, 6, 2]$ which would add the blue arc. However, the right endpoint of the red arc (5) is no longer 'visible'.

Figure 8: This dependency graph has a crossing graph with a cycle of length 4 and is therefore 'almost as hard' as a cog belt. It can be derived in the relaxed deduction system using rule (7): $Int[1, 6] \leftarrow s[1, 4] + Int[1, 2] + L[2, 4, 1] + N[4, 6, 2]$

 $(30) \quad C[i, j, x, y] \leftarrow s[x, y] + s[i, j] + Int[i, y] + Int[y, j]$ $(31) \quad C[i, j, x, y] \leftarrow s[x, k] + Int[i, k] + C[k, j, i, y]$ $(32) \quad Int[i, j] \leftarrow s[i, k] + s[i, y] + s[l, j] + Int[i, l] + Int[l, k] + C[k, j, l, y]$

Figure 9: Additional rules for cog belts.

4.4 Extension to the Full Class

We have just seen that the subgraphs which the relaxed deduction system fails to parse are exactly cog belts. We now show how to extend the system into a complete parser for the full class of 1ec graphs. The key idea is that because cog belts are isolated from the remainder of the graph in terms of crossing arcs as per Lemma 6, we can simply add new items and rules that build a cog belt on top of a set of isolated intervals.

The new items take the form C[i, j, x, y] and represent partial cog belts on an interval [i, j] with two additional vertices: one external vertex x (which always lies to the left of i) and one new internal vertex y, whose purpose is to 'remember' the vertex that will be needed to close the cog belt (cf. Figure 7). The new inference rules are given in Figure 9 and are set up to derive a cog belt right-toleft. Rule (30) starts the derivation, combining two isolated intervals and adding two arcs. Rule (31) extends the cog belt by one isolated interval, adding a new arc. Finally, rule (32) closes the cog belt by adding two final intervals and three new arcs. With this simple extension, the deduction system becomes sound and complete with respect to the full class of 1ec graphs.

Example derivation. To illustrate the workings of the new rules, we provide a derivation of a cog belt with length 6, which in Figure 5 we showed to be non-derivable in the relaxed system. We assume that we have already derived isolated interval items Int[i, i + 1] for all vertices i < n. We then instantiate rule (30) as

$$C[4, 6, 3, 5] \leftarrow s[3, 5] + s[4, 6] + Int[4, 5] + Int[5, 6]$$

and after that rule (31) as

 $C[3,6,2,5] \gets s[2,4] + Int[3,4] + C[4,6,3,5]$

To complete the derivation of the cog belt as a closed interval item we instantiate rule (32) as

$$Int[1,6] \leftarrow s[1,3] + s[1,5] + s[2,6] + Int[1,2] + Int[2,3] + C[3,6,2,5]$$

The asymptotic runtime complexity of the extended algorithm is in $O(n^5)$, one order of magnitude higher than that of the tree-based algorithm. This is due to rules (31) and (32), each of which refers to five independent positions in the sentence.

5 Discussion

In this section we discuss our results and relate them to other published work.

5.1 Graph-Theoretical Results

The main technical contribution of this paper is a characterization of 1ec graphs as a subclass of graphs with pagenumber at most 3 via certain properties of their crossing graphs – in particular the absence of dominoes and the isolation of cycles of length at least five, which induce the substructures that we called cog belts (Section 3). The relations between the various graph classes discussed in this paper are visualized in Figure 10.

lec graphs have previously been discussed primarily in the context of dependency parsing. The characterization in this paper was established using results from graph theory, in particular from the study of circle graphs (Ageev, 1999). Future work of this kind may help to identify new classes of interesting dependency graphs or new parsing algorithms.



Figure 10: Relations between the classes of noncrossing graphs (nc), graphs with pagenumber at most k (pn ≤ 2 , pn ≤ 3), 1ec graphs, and 1ec graphs without cog belts (1ec⁻).

Two classes of graphs that appear to be very relevant for the study of 1ec graphs are *fan-planar graphs* (Kaufmann and Ueckerdt, 2014) and *outer-fan-planar graphs* (Bekos et al., 2014). Their defining property is essentially identical to the 1ec constraint; however, their vertices are not linearly ordered as in dependency graphs,

5.2 Parsing Algorithm

A second contribution of this paper is the extension of the parsing algorithm for 1ec trees (Pitler et al., 2013) to a quintic-time algorithm for the full class of lec graphs, and a quartic-time algorithm for the restricted class of 1ec graphs without cog belts. Closely related algorithms were recently proposed by Cao et al. (2017) and Kummerfeld and Klein (2017). The former use an approach similar to ours in Section 4.4 to parse what they call 'coupled staggered patterns' (our cog belts), albeit restricted to pagenumber 2; they report state-ofthe-art results on the SemEval data. Kummerfeld and Klein (2017) apply 1ec graphs in the context of parsing to phrase structure representations with traces; their algorithm cannot parse what they call 'locked chains' (our cog belts), but has the benefit of enforcing acyclicity and uniqueness.

The proposed quintic-time algorithm may not be the most attractive one for practical parsing. We looked at the SemEval data from Section 2 and found that cog belts occur rarely, less than once per 2,000 sentences, and for only two of the representation types (PSD and CCD). A similar observation was made by Kummerfeld and Klein (2017) for the graphs they obtained from their treebank data.

In presenting our algorithms, our main focus was on theoretical properties (soundness and completeness). To support the implementation of a practical parser, the extended deduction system needs to be refined in several ways. For one thing, the system features a high degree of derivational ambiguity, which in particular can lead to the same arc being scored several times in a derivation. To avoid this, we would need to extend the items with information on whether an arc has already been set, very similar to the booleans used to control treeness in the original algorithm. For example, a modified version of rule (5) could look like this:

$$Int[i, j; F] \leftarrow s[i, k] + LR[i, k, l; F, b_{i,l}, b_{k,l}] + Int[k, l; F] + Int[l, j; b_{l,j}]$$

The LR item has three booleans, corresponding to

the three arcs that could be present among the three sets of endpoints $\{i, k\}, \{i, l\}, \text{ and } \{k, l\}$. The first boolean has to be F (false), as the arc between i and k is scored in the rule; the other two arcs may or may not be already present, so the values of the second and third boolean are free to choose. However, when the arc between k and l was set in the derivation of the LR item, it should not have been already set in the derivation of the Int[k, l]item, which is why we need to set the boolean in this item to F.

The modified version of rule (5) is actually a *rule template* which in an actual parser implementation needs to be instantiated in all legal ways. This introduces a non-negligible constant factor into the runtime: assuming a minimal number of three boolean variables per rule and a fourth binary choice for the direction of the arc (which we have left underspecified), we would already get $32 \cdot 2^4 = 512$ actual rules. This ignores the additional bookkeeping that needs to be added in order to prevent cycles or enforce uniqueness of derivations, each of which would at least double the number of rules, and the increased complexity coming from labelled parsing.

The most promising parsing results so far on the SDP data have been achieved with a simple, quadratic-time parsing algorithm with very few constraints on the search space but a strong learning component (Martins and Almeida, 2014; Peng et al., 2017). A structurally restricted parsing algorithm such as the one described in this paper, even if its coverage is high, has the drawback that it is harder to combine with an expressive learning approach such as the recurrent neural networks used by Kiperwasser and Goldberg (2016).

6 Conclusion

We have shown how a new structural characterization of 1ec graphs in terms of their crossing graphs can be used to extend the parsing algorithm for 1ec trees to the full class of graphs. The class of 1ec graphs has a significantly higher coverage than the previously considered class of noncrossing graphs (Schluter, 2015; Kuhlmann and Jonsson, 2015) and may thus be a useful constraint on the search space for deep dependency parsing. However, to achieve state-of-the-art results the new parsing algorithm needs to be combined with a powerful machine learning component, a practical challenge that we leave to future work.

Acknowledgements

We thank the anonymous reviewers for their helpful comments. This work was supported by a Google Faculty Research Award to Marco Kuhlmann.

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